Gasoline Price Dispersion and Search: Evidence from a Natural Experiment

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September 1, 2017

Abstract

This article examines the effect of price dispersion on actual search activity, contrasting most previous studies that examine the reverse effect of search activity on price dispersion. Exogenous cost-based and price-cycle-based shocks to retail gasoline price dispersion are explored, and a natural experiment – in the form of a refinery fire that caused decades-old price cycles to stop and price dispersion to change in a particular non-linear way – is also used to identify effects. A direct measure of search is used. The results show a substantial response in search intensity from external shocks to price dispersion.

JEL Classification Codes: L11, L15, L81, L91, Q31

Keywords: Price Dispersion, Search, Search Costs, Retail, Gasoline, Edgeworth Price Cycles

1 Introduction

Economists have long studied the causes and consequences of consumer search. For good reason – understanding how and why consumers search has important implications for competition, prices, profits and consumer welfare. Stigler (1961)'s seminal theoretical result is essentially that consumers equate the marginal benefit of additional price search to the marginal cost of additional search, and since that time a large game-theoretic literature has emerged to study search in an equilibrium setting. While predictions do not always agree, a common result is that the greater the costs of search, the less search there is, the higher are consumer prices, and the greater is price dispersion in equilibrium.

A large empirical literature examining this relationship has followed. Much of this research seeks to explain observed price dispersion as a function of differences in search costs (or, more

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rarely, search benefits). One limitation of the literature is that direct measures of search costs or, indeed, search activity itself, are rarely available. As a result, search costs are often inferred from product or market characteristics and it is presumed that unobserved search activity responds to changes in these proxies in expected ways.

While most studies examine the effect of search costs on price dispersion, very little work has been done to measure the reverse effect of price dispersion on search. Price dispersion can arise for many reasons, not just search-based reasons, and an increase in price dispersion from these other sources can lead to greater search by increasing the benefit of doing so. Relatively little is known about this demand-side relationship, and a direct measure of search is necessary to explore it.

In this article, I estimate the effect of plausibly exogenous changes in price dispersion on actual search activity. I examine a world where search costs are relatively constant over time, and variation in price dispersion is largely generated by supply-side processes that create temporal variation in the benefits of search and, potentially, in actual search. It is one of the few studies to employ a direct measure of search to investigate the question. It is the first, to my knowledge, to simultaneously examine changes in price dispersion due to multiple distinct processes, and the first to use a natural experiment to identify effects. The natural experiment is one in which price dispersion suddenly and substantially changed in a non-linear way due to non-search related reasons.

The empirical analysis focuses on retail gasoline markets in a set of large Canadian cities. Retail gasoline is an interesting laboratory to study search for a number of reasons. First, unlike many other industries, direct measures of search are available. In this study, I use search activity from GasBuddy.com, a gasoline price reporting website and app. A network of volunteer price spotters upload and share gasoline price information with other users of the site. The number of price reports submitted to the website serves as a measure of search activity. Second, and importantly, changes in price dispersion from supply-side forces, independent of search, are common in retail gasoline markets.

I identify and examine three different sources of temporal variation in price dispersion. First, prices change frequently in large markets in response to constantly changing crude and wholesale costs. The increased temporal price dispersion leads to increased cross-sectional price dispersion as changes are implemented unevenly across stations, by different amounts at different times. I test

whether search intensity increases as temporal and cross-sectional price dispersion increases.

Second, several markets exhibit tall and high-frequency asymmetric price cycles. The cycles have been well studied and create substantially higher temporal and cross-sectional price dispersion at select specific points along the cycle. I test whether search intensity is higher at precisely those points of the cycle that regularly exhibit the greatest degree of price dispersion.

Third, I exploit a unique natural experiment, in the form of a refinery fire that, in a matter of days, caused decades-old price cycles – and the distinct patterns of price dispersion along them – to suddenly stop in a set of nearby cities. The cessation of cycles caused a sudden and non-linear change in temporal and cross-sectional price dispersion patterns. The new equilibrium took the form of almost constant daily margins in one city, with especially little variation in dispersion. Chandra and Tappata (2011) state that "it is important to find a control group or benchmark" for identifying the relationship between search and price dispersion, and the post-fire experience in these cities serves that purpose well. I test whether the unique pattern of temporal search intensity that had existed when the price cycles were present meaningfully changed once the price cycle, and the usual non-linear pattern of price dispersion along it, came to a sudden end. Alternatively, I test whether search intensity became more uniform over time when the cycles ceased. I find that there is an effect of price dispersion on search activity from all three sources.

The current work is most closely related to Lewis and Marvel (2011), Byrne et al. (2015), and Byrne and de Roos (2015), who examine the effect of price dispersion on search in various gasoline markets. Lewis and Marvel, examining the U.S., focuses largely on the first source of price dispersion. The latter two studies, one examining smaller cities in Ontario, Canada, and the other examining Perth, Australia, focus on the second. The use of a natural experiment to identify exogenous and non-linear shocks to price dispersion patterns is new.

To preview results, I find that greater price dispersion leads to greater actual search activity, but that the effects vary with the source of the change. Consistent with Lewis and Marvel (2011), I find that search intensity is greater when prices are rising in response to increases in the wholesale price, compared with periods of stable prices. In contrast to that study, however, I find that search intensity is also greater when prices are falling due to changes in the wholesale price, compared with a stable price world. Overall, I find a negative response asymmetry – search activity ramps

up more when prices are falling than it does when they are rising.

In terms of price dispersion in the context of retail gasoline price cycles, I find that search is greatest just before and during the period when prices rise quickly (and price dispersion is at its greatest). I find search intensity to be lowest "mid-cycle" when price dispersion is also lowest. The result is consistent with previous work in other markets. However, I point out a multicollinearity problem between the periodic nature of price cycles and the periodic nature of the "natural" search cycle (the search pattern that otherwise have existed in the absence of price cycles), which can potentially bias results and has traditionally been difficult to handle.

Fortunately, I can circumvent the problem by exploiting the aforementioned natural experiment. The experiment breaks the multicollinearity by isolating the natural search cycle after the price cycles had come to a stop. I find that, after the fire and after the cycles ceased, search intensity decreased the most at precisely those times when price dispersion would have been highest during the cycle. At other times where price dispersion had already been relatively low, I find little change in search intensity after the cycles ceased. In other words, the sudden change to a more uniform level of price dispersion over time resulted in a more uniform level of search intensity over time. Meanwhile, where retail price cycles continued unabated far away from the location of the fire, I find no change in the non-linear pattern of search. The multiple controls add to the strength of the results. In summary, I find that the large and exogenous shock to price dispersion occurring only in some markets and at certain times caused an almost immediate and matching shift in search intensity but only in those same markets at those same times.

2 Literature and Background

The costs and benefits of search have played a pivotal role in the theoretical literature on price dispersion. In a seminal article, Diamond (1971) finds that if all consumers have positive search costs, price dispersion falls to zero, prices rise to monopoly levels, and there is no search in equilibrium, as the benefits to search are erased (the "Diamond paradox"). Difficult to reconcile this result with real world experience, Varian (1980) and Stahl (1989) develop models in which some consumers have positive search costs and some consumers have zero search costs. In these models,

they find that (cross-sectional) price dispersion does occur in equilibrium.

The theoretical work has spawned many authors to empirically test whether differences in search costs (or search benefits) have an effect on price dispersion and prices. Many are cross-sectional in nature. Sorensen (2000) compares price dispersion in pharmaceuticals for acute versus chronic illnesses, and finds price dispersion is lower for the latter (where repeated purchases make the benefits of search greater). Brynjofsson and Smith (2000) find that price dispersion is lower for goods sold on-line, where search costs are likely to be lower. Gerardi and Shapiro (2009) find that competition among airlines reduces price dispersion, while Borenstein and Rose (1994) in an earlier work find an opposite result. Other studies examining the link include Dahlby and West (1986) on auto insurance, Walsh and Whelan (1999) and Zhao (2006) on groceries, Baye, Morgan and Scholten (2004) for on-line purchases, Milyo and Waldfogel (1999) on liquor, and many others. In most studies, search and search costs are not measurable directly but are inferred from various factors, including the type of product involved, the presence of advertising, the frequency of purchases, the visibility of price, the degree of competitor closeness, and other factors.

Several authors have examined the effect of search costs on price dispersion in retail gasoline markets specifically, although typically absent a direct measure of search or search costs. Barron et al. (2004) find less price dispersion with more densely located stations (which should lower consumer search costs). Lewis (2008) finds less price dispersion when there are more competing stations of a similar brand type, but more dispersion when a mix of brand types are present. Tappata and Chandra (2011) find that stations at the same intersection exhibit less price dispersion and that premium prices show more dispersion, consistent with a search cost explanation.[1]

Articles using direct measures of search are less common. Among the first relating to gasoline markets is Lewis and Marvel (2011), who measure search using hits to the gasoline price reporting website, GasBuddy.com. They find that search activity increased when prices were rising, but changed relatively little when prices were falling, consistent with the theoretical reference price model of Lewis (2011). The result can provide a potential explanation for the well known "rockets and feathers" effect found in U.S. markets (Borenstein et al. (1997) and many others).[2]

[1] Hosken et al. (2008) quantify the degree of dispersion across stations in Washington, D.C., and opine that it is relatively high considering the homogeneity of the product.

[2] Noel (2009) finds that asymmetric price cycles alone can result in a finding of rockets and feathers, even when

Recently, several articles have explored search in the context of retail gasoline markets where high-frequency gasoline price cycles are present. High-frequency gasoline price cycles have been documented in several countries over the past few decades – e.g. Canada (Eckert (2003) and Noel (2007a)), the United States (Castanias and Johnson (1993) and Lewis (2009)), Australia (Wang (2009b)), Norway (Foros and Steen (2013)), and Germany. Figure 1 shows a picture of a retail gasoline price cycle in the city of Toronto and in the city of Windsor, two of the sample cities used in this study. The period of the Windsor cycle is about a week on average, and the period of the Toronto cycle is exactly a day. The leading theory behind the price cycles is the Edgeworth Price Cycle model of Maskin and Tirole (1988), as extended by Eckert (2003) and Noel (2008). In an Edgeworth Price Cycle, firms undercut one another in a tit-for-tat fashion until prices reach marginal cost, at which point one firm raises its price to a higher level, others follow, and undercutting begins again.

Some general results have emerged about how gasoline price cycles function. Cycles are more likely to occur when there are more price aggressive firms (Noel 2007a) and where station-level price elasticities are very high (Noel (2008), Wang (2009a)). Large firms tend to increase prices first and small firms tend to decrease prices first (Noel (2007b), Lewis (2012)), while mom-and-pop type stations are least likely to follow changes along the price cycle (Doyle et al. (2010)). Also, Noel (2002), Doyle et al. (2010), Zimmerman et al. (2013), and Noel (2015) all find price cycles lead to lower prices, while de Roos and Katayama (2013) and Foros and Steen (2013) continue to express collusive concerns. Most studies that examine gasoline price cycles find them to have a period of a week or two, though price cycles with a daily period have recently been found and analyzed in large Canadian cities (Atkinson et al. (2014), Noel (2015)).[3]

A useful feature of retail gasoline price cycles, for the purposes of this study, is that they create substantial and predictable price volatility over time. With that temporal price dispersion comes a particular pattern of cross-sectional price dispersion as well. The literature has shown that cross-

the cycle taken as a whole moves symmetrically in response to price increases and decreases. Comparing cities with and without cycles, Lewis and Noel (2011) find that markets with asymmetric price cycles in the U.S. are also more price fluid markets and lead to less asymmetry in passthrough overall.

[3] Using daily data for a set of cities in Ontario, Canada, Byrne (2015) finds that price cycles were most common in medium sized cities and less common in large cities. However, any price cycles in larger cities that exhibit a daily periodicity, such as those studied here, would not be visible in his daily price data.

sectional price dispersion along gasoline price cycles is greatest during the "relenting phase" of a price cycle, i.e. the few days (or few hours) in which firms increase prices in a staggered fashion. During this time, some firms have increased prices by as much as 10% or more while others are yet to do so (Eckert and West (2004), Noel (2007b), Doyle et al. (2010), Noel (2012) and others), causing a spike in cross-sectional price dispersion. Price dispersion tends to be at its lowest right after firms have all finished increasing prices, and then gradually increases a little as firms undercut each other at slightly different rates in different neighborhoods (Eckert and West (2004), Bloch and Wills-Johnson (2010), Lewis (2012), and others). The non-linear pattern of price dispersion over the path of the cycle will be useful for identify the effects on search, later.

Byrne et al. (2015) examine search in the context of retail gasoline price cycles. They use a direct measure of search, similar to that used here, and examine consumer search over the relenting and undercutting phases of the cycle. In their sample of small and mid-sized Ontario cities, they find that search is greatest just before and just as prices start to rise.[4] Byrne and de Roos (2015) find a similar result for Perth, Australia.[5]

A challenge in estimating the effect of price dispersion on search, in the context of price cycles, comes from the fact that price cycles, and its unique pattern of price dispersion, often follows a weekly (or sometimes daily) pattern. Simultaneously, there is natural variation in search activity, even in the absence of price cycles, in which search tends to follow a weekly (and daily) pattern as well. Absent controls, the collinearity between the price cycles and the natural search cycle could result in a spurious relationship. For example, in many cities, price increases often occur mid-week, the same time that one would expect search to be high even in the absence of price cycles. The

[4] Byrne et al. (2015) show that consumers search more often (and are assumed to purchase more often) at the troughs of the price cycle, while searching (purchasing) very little in the few days after the peak. They state that the result provides some of the first hard evidence of stockpiling in retail gasoline markets. However, it is well known that many consumers time their purchases and buy more frequently at the troughs of the price cycles and less at the peaks (ACCC (2007), Foros and Steen (2008), Wang (2009a), Noel (2012), Noel and Chu (2015), and others). Since gasoline is a durable good and there are transaction costs in going to a gasoline station, it would be unlikely for consumers to purchase gasoline twice on consecutive days, and unlikely for those timing the troughs to purchase a day or two later at the peaks. In this sense, a small degree of stockpiling is natural and well known. Chandra and Tappata (2011) point out that stockpiling in the more strategic sense is unlikely to be feasible in gasoline markets, as it is difficult (and rare) for consumers to purchase more than a tank full, even when they suspect prices are low. An interesting and open question is whether consumers also adjust their average dollar spend based on price expectations, instead of simply timing purchases to the troughs.

[5] Under Perth's FuelWatch price notification regulation, firms are required to announce their prices a day in advance. Prices are then posted to a government website and available for consumer search.

smallest price dispersion is expected mid-cycle, which most often falls on a weekend, when search activity is normally low.

Controlling for weekly effects with day of the week variables is the obvious fix, but can potentially overcompensate by soaking up variation in search that is truly due to price dispersion but cannot be separated from the day of the week pattern. The greater the collinearity between the price cycle and the natural search cycle, the greater is the difficulty in econometrically separating the two. Excluding day of the week affects can cause upward biases, including them can cause downward biases or inflated standard errors. In some cases, the price cycle can be perfectly correlated with the day of the week. In Byrne and de Roos' study of Perth, all relenting phases occurred on Thursdays during their sample period and day of the week controls are not possible. The authors must appeal to the implausibility of a natural weekly search cycle that would so dramatically peak on a Wednesday and Thursday, if not for the cycles.[6] While reasonable, ideally, one would like to identify and remove the effect of any natural underlying search cycle to focus alone on identifying the effect of price dispersion on search.

One of the novel features of this article is the use of a natural experiment that can do just that. On February 15th, 2007, a refinery fire in the town of Nanticoke, Ontario, caused price cycles that had existed for decades in several nearby cities, including Toronto and London, to suddenly cease. Atkinson et al. (2014) examined possible causes for the cessation of cycles and identified the fire as the obvious cause. Within days of the fire, the cycles were gone and replaced with less volatile cost-based prices. In the city of Toronto in particular, prices became flat during the day and almost perfectly correlated with rack prices over time, yielding an almost constant average 5 cent per liter margin. The fire was a clear supply-side exogenous shock to the pattern of price dispersion, and can be used to identify changes in search intensity. It is a rare opportunity to examine search and price dispersion, as equilibrium shifts between cycle and non-cycle regimes are exceedingly rare.[7]

To my knowledge, this is the first study to explore search in retail gasoline markets, using a direct measure of search, in the context of both cyclical and non-cyclical gasoline pricing regimes

[6] Cycle peaks synchronized to the day of the week or time of day are common in Canadian, Australian, and Norwegian markets (Atkinson et al. (2014), Noel and Chu (2015), Foros and Steen (2013)).

[7] This should be distinguished from temporary breakdowns in the cycling pattern (delayed starts and false starts in the language of Noel (2008)).

and in the face of an exogenous shift between the two.

3 Data and Methodology

I examine daily price and search data for six Canadian cities - Toronto, London, Windsor, Winnipeg, Calgary, and Vancouver, over two years from March 2006 to February 2008. The first three cities are in the province of Ontario; the latter three are in Western Canada. The data was purchased from GasBuddy.com, a popular gasoline price reporting website and app. The daily price data used in this study is the average price from of all gasoline price reports to the website for a given city in a given day.

One of the most difficult challenges for studying search is obtaining a reasonable measure of the amount of price search that occurs. Among the first to use a direct measure of search is Lewis and Marvel (2011) who use visits to the U.S. GasBuddy website, as counted by users of a particular browser toolbar. One limitation of the measure is that it is only at the national level and cannot be matched to market level price changes. Byrne et al. (2015) use a market level measure of search, the number of unique price reports submitted by price spotters to the GasBuddy website. The measure implicitly assumes that consumers more actively search at the same times that spotters more actively collect prices. While imperfect, the proxy is reasonable given that the point of reporting prices is to help consumers learn gasoline prices, and the implicit value of doing so increases with the number of consumers who wish to learn those prices. This measure is among the best currently available to researchers for a wide range of gasoline markets. In this study, I use the number of unique price reports reported to the GasBuddy site in a given city on a given day as a measure of daily search intensity.

In terms of spotters' reporting accuracy, Atkinson (2008) finds that the GasBuddy data does a generally good job in representing street prices, based on a comparison of GasBuddy's prices for Guelph, Ontario, and the author's own collection of prices in that town. The author notes that some stations can be underrepresented and infrequently collected, a problem that is more likely to occur in smaller towns where the number of price reports are relatively few.

I consider only larger and well covered cities with a minimum of ten price reports per station

per month. The six cities above meet that criteria. The number of price reports per station per month range from approximately fourteen in Windsor to over one hundred in Toronto. The total number of price reports per day range from 32.4 per day in Windsor to 1404.3 per day in Toronto.[8]

The baseline model taken to the daily level dataset is given by:

$$\ln(ReportCount)_{jt} = \alpha + \delta^{+}\Delta p^{+}_{j,t+1} + \delta^{-}\Delta p^{-}_{j,t+1} + \sum_{i=0}^{M-1} \beta^{+}_{i}\Delta p^{+}_{j,t-i} + \sum_{i=0}^{M-1} \beta^{-}_{i}\Delta p^{-}_{j,t-i}$$
$$+\mu^{DOW}_{t} + \mu^{YM}_{t} + \mu^{CITY}_{j} + X_{jt}B + \varepsilon_{jt} \tag{1}$$

where $ln(ReportCount)_{jt}$ is the natural log of the number of price reports for a given market j at time t, $\Delta p^{+}_{t} = \max(0, \Delta p_t)$ and $\Delta p^{-}_{t} = \min(0, \Delta p_t)$ where $\Delta p_t = p_t - p_{t-1}$ is the daily change in the retail price of regular grade gasoline, and M is the number of included lagged price changes. I set $M = 14$, allowing for up to a two week memory. Results are similar for larger values of M. I freely estimate the coefficients on the contemporaneous daily price change, β^{+}_{0} and β^{-}_{0} which I expect to be of most importance and, following Lewis and Marvel (2011), constrain ranges of coefficients for later lagged price changes. In the main specifications, I set $\beta^{+}_{WEEK1} = \beta^{+}_{1} = \ldots = \beta^{+}_{6}$ to capture the average effect of lagged price increases from the the rest of the previous week on search, and β^{-}_{WEEK1} in a similar way to capture the effect of lagged price decreases. I then set $\beta^{+}_{WEEK2} = \beta^{+}_{7} = ... = \beta^{+}_{13}$ and β^{-}_{WEEK2} similarly to represent the average effect of positive and negative lagged price changes, respectively, from the week prior to the previous week on search. Results are not sensitive to the particular choice of ranges for the constrained coefficients.

The specifications also include lead price changes, Δp^{+}_{t+1},and Δp^{-}_{t+1}, for positive and negative changes, to capture any predictive effect on search intensity. There are several reasons why lead

[8] I also inquired about the cities of Montreal, Quebec City, and Ottawa, but they were excluded due to insufficient numbers of price reports. The English-only GasBuddy sites were less popular for drivers in the largely French-speaking cities of Montreal and Quebec City and the multi-lingual Ottawa-Gatineau area. Whereas in the six cities where GasBuddy was well established the number of price reports was large and trending slightly downward, the number of price reports in Montreal, Quebec City and Ottawa were fewer (less than four per station per month) and had the reverse trend. The Montreal and Quebec City sites only started in June 2006, part way through the sample. Also, in the four-times-a-day data, discussed later, the number of price reports in the three excluded cities were zero for approximately a third of the intraday periods, resulting in missing intraday price information. In the included cities, price reports were non-zero in every intraday period and the pricing series were complete. Since this article deals with price changes (as opposed to price levels), with different treatment for increases and decreases, good coverage is important.

price changes could matter. First, it is well known that retail gasoline prices respond to crude prices with a lag, so that crude price changes, and later rack price changes, give some scope for predictability. Second, refinery or other problems which are expected to cause imminent price spikes are often reported in the press. Third, the switchover to summer and winter blend fuels and scheduled refinery maintenance both follow a predictable seasonal pattern. Fourth, the presence of retail price cycles, discussed in more detail later, can also make price increases potentially predictable (Noel (2012), Noel and Chu (2015)) and lead to more search (Byrne et al. (2015)). Finally, with or without price cycles, price increases appearing at a few local stations can signal that additional price increases are likely to spread across the market.

The specifications include indicator variables for the day of the week (μ_t^{DOW}), year-month combinations (μ_t^{YM}), and city (μ_j^{CITY}). Day of the week indicators recognize that search has a highly cyclical day of the week pattern, with more search during the workweek and less on weekends. Year-month indicator variables account for the slow declining trend in search over the sample period. In alternate specifications, I use a time trend and various polynomials of time trends instead of year-month indicators, with similar results. The econometric error terms, ε_{jt}, are assumed to be normally distributed and clustered at the city level. The $X_{jt}B$ contains additional regressors in the robustness specifications discussed later.[9]

One concern is that lagged and lead retail prices may be endogenous to search since search levels can have a rebound effect on firm margins and prices. To address this, I also perform a set of instrumental variables specifications using lagged and lead rack prices as instruments. Results from the instrumental variables regressions are similar to those from the baseline least squares regressions.

Gasoline price cycles are present in four of the six markets in the dataset. One city (Windsor) exhibits weekly to biweekly period price cycles, visible in the daily data. The Windsor cycles have been studied by Eckert (2002) in another context, and is a city examined by Byrne et al. (2015). I estimate the following model for the city of Windsor, in addition to Equation 1, to account for the particular asymmetric form of temporal and cross-sectional price dispersion known in that market:

[9] Dickey-Fuller tests reject the null hypothesis of a unit root in the log of the number of price reports in each city at the one percent level, in favor of stationarity. Similarly, the null hypothesis of a unit root in lead, contemporaneous, and lagged price changes is rejected in each city at the one percent level.

$$\ln(ReportCount)_{jt} = \alpha + \delta^{+}\Delta p^{+}_{W,t+1} + \delta^{-}\Delta p^{-}_{W,t+1} + \sum_{i=0}^{M-1} \beta^{+}_{i}\Delta p^{+}_{W,t-i} + \sum_{i=0}^{M-1} \beta^{-}_{i}\Delta p^{-}_{W,t-i}$$

$$+\gamma_1 SECOND\_DAY\_PRIOR_t + \gamma_2 FIRST\_DAY\_PRIOR_t + \gamma_3 START\_OF\_RELENT_t$$

$$+\gamma_4 END\_OF\_RELENT_t + \gamma_5 FIRST\_DAY\_AFTER_t + \gamma_6 SECOND\_DAY\_AFTER_t$$

$$+\phi^{DOW}_t + \phi^{YM}_t + \phi^{CITY}_j + \upsilon_{jt} \tag{2}$$

where the terms presented in the first line of the equation are as above, and $j = W$ denotes Windsor. The latter two lines include variables that explicitly account for cycle timing. I define the day that market average prices begin to rise (by at least one cent over the previous day) as the $START\_OF\_RELENT$ day. As this day progresses, the first firms begin to increase their prices the full height of the price cycle, resulting in a large degree of price dispersion between stations who have already increased prices and those that have not (the average cycle amplitude exceeding six cents per liter in Windsor). The process generally continues into a second day, the END_OF_RELENT day, in which additional stations increase price and the market price may rise further. The market price never rises by more than a cent on the third day during the sample. The indicator variables $SECOND\_DAY\_PRIOR$ and $FIRST\_DAY\_PRIOR$ represent the second and first days, respectively, before the $START\_OF\_RELENT$ day, and $FIRST\_DAY\_AFTER$ and $SECOND\_DAY\_AFTER$ are the first and second days, respectively, after the END_OF_RELENT day.

The other three cities that exhibit price cycles – Toronto, London, and Vancouver – exhibit daily price cycles. Daily price cycles have rarely been studied in the literature but are essentially sped up versions of weekly price cycles. They are not visible in daily-level price data, the frequency of data used in the vast majority of recent articles on gasoline prices, and all those to my knowledge using direct measures of search. Intraday data is needed.

I therefore augment the daily data with a two month sample of four-times-a-day data for the three sample cities that exhibit daily price cycles. The data, from GasBuddy.com, includes

gasoline prices and the number of price reports within each intraday reporting period.[10] The intraday periods are 6am-10am, 10am-2pm, 2pm-6pm, and 6pm to midnight, and span from the morning of January 15, 2007 to the evening of March 13, 2007. Summary statistics for both the four-times-a-day dataset and the daily dataset are reported in Table 1.

I first estimate the following equation with the four-times-a-day data:

$$\ln(ReportCount)_{jt} = \theta + \lambda^{+}\Delta p^{+}_{j,t+1} + \lambda^{-}\Delta p^{-}_{j,t+1} + \sum_{i=0}^{N-1}\kappa_i^{+}\Delta p^{+}_{j,t-i} + \sum_{i=0}^{N-1}\kappa_i^{-}\Delta p^{-}_{j,t-i}$$
$$+\phi_t^{DOW} + \phi_t^{IDP} + \phi_t^{YM} + \phi_j^{CITY} + \nu_{jt} \tag{3}$$

where ϕ^{IDP} is an indicator variable for the intraday period (second through fourth, with the first intraday period omitted), and other variables are as before. The value of N is set at 8 to capture short run search dynamics over several cycles. The results of interest are very similar with higher values of N. I freely estimate κ_0^{+} and κ_0^{-} and set $\kappa^{+}_{DAY1} = \kappa_1^{+} = ... = \kappa_3^{+}$, $\kappa^{+}_{DAY2} = \kappa_4^{+} = ... = \kappa_7^{+}$ (the rest of the first day and then the second day) for readability. I define κ^{-}_{DAY1} and κ^{-}_{DAY2} similarly. As before, results are not meaningfully affected using other constrained ranges.

There are no separate cycle timing variables (e.g. $START\_OF\_RELENT$) in the specification as these are almost perfectly correlated with the intraday period variables, ϕ_t^{IDP}, as discussed below. For example, $START\_OF\_RELENT$ and END_OF_RELENT are both essentially equivalent to ϕ_1^{IDP}, the first intraday period.

After discussing multicollinearity concerns between daily (weekly) price cycles and the natural daily (weekly) search cycle that could potentially affect the above results, I turn to an analysis of the natural experiment which avoids such concerns. The Nanticoke refinery fire caused the cycles suddenly cease in Toronto and London (Noel (2015)) and caused the pattern of price dispersion in those markets to change in a particular non-linear way. It had no effect on the daily price cycles in Vancouver (Noel (2015)).

I examine the effect of the shock using a set of city-specific difference-in-differences regressions:

[10] I also collected samples of four-times-a-day data in the other cities and confirmed there were no daily cycles there.

$$\ln(ReportCount)_{jt} = \zeta_{0j} + \phi_{jt}^{IDP} + \zeta_{1j}AFTER_t + \zeta_{j2}AFTER_t * \phi_{jt}^{IDP} + \phi_{jt}^{DOW} + \eta_{jt} \quad (4)$$

where the first intraday period fixed effect, ϕ_{j1}^{IDP} is the omitted intraday variable.

The primary test is whether search intensity decreased the most at precisely those points along the cycle when price dispersion had been at its highest in the affected cities. Price dispersion is highest in a cycle during the relenting phase, which occurs almost exclusively in the first intraday period in the three cities with daily price cycles. Price dispersion is also generally modestly higher at the cycle troughs than mid-cycle. I test whether ζ_{1j} is significantly different from zero (the change in search intensity during the first intraday period), and whether each $\zeta_{j1} + \zeta_{j2} * \phi_{js}^{IDP}$ is significantly different from zero for each $s \neq 1$ (other intraday periods), and for each city j. The null hypothesis is that the non-linear pattern of search intensity across the cycle (very high, low, low, medium) did not change in any city after the fire. The alternative is that search intensity disproportionately decreased in the first intraday period and, potentially to a lesser extent, the fourth intraday period, and only in Toronto and London but not in Vancouver, whose cycles did not change.

An alternative test examines the volatility of search over the course of a day in each city, both before and after the fire. Under the alternative, the pattern of search intensity across the four intraday periods should become more uniform in the cities of Toronto and London after the fire, but not in the city of Vancouver. The reasoning is as follows. In the presence of cycles, there are two sources creating a non-uniformity in search intensity over the course of the day. First, there is a natural daily search cycle in which search is more likely in the first and fourth intraday periods, as these include the morning and evening rush hours. Second, under the alternative, search will also be higher during the first and fourth periods, and most notably the first, since prices are more volatile and disperse in these periods. The first intraday period contains the relenting phase of the cycle, when price dispersion is especially high. The fourth intraday period contains the cycle troughs, which may exhibit a little more price dispersion as well. The two effects compound to create a stronger non-linear U-shaped temporal pattern of search from morning to night. In the

absence of price cycles, only the natural daily search cycle remains and search should be relatively more uniform, under the alternative hypothesis that price dispersion increases search. Meanwhile, in Vancouver, both the price cycle and the natural search cycle continue to be present before and after the fire and there should be no decrease in uniformity of search throughout the day there.

4 Results

4.1 Price Dispersion due to Rack Price Changes

I begin with an analysis of search intensity in response to price dispersion stemming from daily rack price changes. This analysis focuses on the daily level dataset, as rack changes are daily. Table 2 reports the main results. Specification (1) includes year-month indicator variables to control for trend and Specification (2) includes a time trend variable in place of year-month indicators. Specifications (3) and (4) are instrumental variables versions of Specifications (1) and (2) respectively.

In Specification (1), I find a statistically significant effect of cost-driven price changes on search intensity. The coefficient on Δp_t^+ is 0.014, meaning that a one cent contemporaneous price increase increases search by 1.4%.[11] The result is consistent with Lewis and Marvel, who find search intensity to increase when prices are on the rise. However, I find the coefficient on Δp_t^- is -0.031, so that a one cent contemporaneous decrease in price increases search by 3.1% (since price decreases are negative, a negative coefficient means that larger price decreases lead to more search). This result differs from that of Lewis and Marvel who generally find no effects when prices fall. The estimates are significant at the 1% and 5% level respectively.

Turning to asymmetry, I find a statistically significant difference between the two estimates in absolute value. In contrast to Lewis and Marvel who find a positive asymmetry (price increases trigger more search than decreases), I find the opposite asymmetry – price decreases trigger more search than price increases. Spotters tend to be more active when prices are changing generally but most active when prices are falling day to day.

[11] Although the dependent variable is in logs, the coefficients do not correspond exactly to percentage changes in search intensity. The percentage increase in search intensity after a one cent change in price is given by exp(b)-1 where b is absolute value of the relevant coefficient (noting that the effect of a one cent decrease in price is exp(-(-b))-1). For small changes (below 3.1%), the coefficient closely approximates the percentage. Here, exp(0.014)-1=0.01409.

The geography and time frame between this and the previous study differ, but it is worth exploring other possible reasons for the difference in results. The Lewis and Marvel result is consistent with the Lewis (2011) model of search-driven rockets and feathers, where greater search causes the price distribution to compress when prices are rising, and to decompress when prices were falling. However, if instead rockets and feathers were at least in part due to other factors, the greater price dispersion when prices are falling could give rise to increased search (a demand-side search response to a supply side price dispersion driver), and produce the result shown here. I note that there is relatively less evidence for a strong rockets and feathers pattern in Canada than in the United States (Godby et al. (2000)). An alternate explanation for the negative asymmetry is psychological rather than financial. There may be a gaming effect in which price spotters and consumers receive additional utility from spotting and buying at a new low price that has not been seen in awhile. In the same spirit, there may be a fatigue effect when prices are rising causing search to temporarily tail off.[12]

The specifications also include lead price changes, Δp_{t+1}, for positive and negative changes. In Specification (1), I find a statistically significant effect of a next period price increase on search (an increase of 2.4%) and a statistically significant effect of a next period price decrease on search (an increase of 2.1%), at the 1% and 10% levels respectively. I find no significant asymmetry between the two.

The specifications also allow for search intensity to respond to less recent price changes, up to two weeks old. The coefficients on Δp^{+}_{WEEK1} and Δp^{+}_{WEEK2} (i.e. β^{+}_{WEEK1} and β^{+}_{WEEK2}) show the effect for price increases over the past week (not including the most recent price change, Δp^{+}_{t}) and for the week prior, respectively. The coefficients on Δp^{-}_{WEEK1} and Δp^{-}_{WEEK2} are similar for price decreases. As expected, the magnitude of these effects are smaller than for contemporaneous or lead price changes (ranging from 0.2% to 0.7% instead of 1.5% to 3.1% with contemporaneous and lead price changes). They are statistically significant in three of four cases. The coefficients on negative price changes are negative as expected (more extended price drops lead to higher search

[12] I have heard anectodes to this effect, and have experienced it once myself. When prices spiralled downward in February 2016, I periodically checked on GasBuddy and managed to find and purchase gasoline for $1.29 per gallon. When prices rose again, searching was not as interesting. Whether the negative asymmetry holds more generally, and why, is an area for future research.

intensity) and the coefficients on positive price changes are also, perhaps surprisingly, negative. The latter suggests that search intensity is slightly lower after several days of sustained price increases compared with the first day of a price increase, consistent with a fatigue story. The estimates, however, are small, and the significance on the positive price change coefficients is not robust across specifications.

Specification (2) uses a linear time trend in place of year-month indicator variables. The effect of a contemporaneous one-cent price increase is to increase search intensity is 1.5% and the effect of a one-cent decrease is to increase search intensity 2.9%, both significant at the 5% level. Again, the two effects are significantly asymmetric, with price decreases triggering more search than price increases. The effect of next period price changes on search intensity is to increase search by 2.5% and 1.9%, for price increases and decreases respectively, significant at the 1% and 10% levels. They are not significantly different from each other, however. There is some evidence that past price changes over the past few weeks affect search, with two of four coefficients statistically significant at the 10% level, but again they are economically small (0% to 0.6%).

Specifications (3) and (4) use rack price changes as instruments for corresponding retail price changes. In Specification (3), the coefficients on the contemporaneous price changes, Δp_t^+ and Δp_t^-, are 0.035 and -0.069 for price increases and decreases respectively, implying a 3.6% increase in search intensity after a one cent price increase and a 7.1% increase in search intensity after a one cent price decrease. Both are statistically significant at the 5% level and again significantly different from one another in absolute value, yielding a negative asymmetry.[13] The coefficients on the next period price changes are larger, 0.058 and -0.091 for price increases and decreases respectively (6.0% and 9.5% increases in search) but neither are statistically significant. The effect of past price changes, both positive and negative, continue to be very small and are no longer significant at the 5% level, with only one coefficient out of four significant at the 10% level.

Specification (4) uses a time trend in the instrumental variables regression and yields a similar result. Contemporaneous price changes are important, with price decreases triggering more search than increases. Lead price changes are similarly large in magnitude, but not significant. Notably,

[13] First stage F statistics, from regressions of past, contemporaneous and lead retail price changes on past, contemporaneous and lead rack price changes are all above 20, with the majority above 80.

none of the small effects from past price changes are statistically significant anymore, both for positive and negative price changes.

To check robustness, I perform a series of additional regressions and report them in Table 3. Specifications (5) and (6) report results from ordinary least squares and instrumental variables regressions using a quadratic time trend instead of linear time trend, with similar results. Specifications (7) and (8), for the least squares and instrumental variables versions respectively, add price as a regressor.[14] Interestingly, the coefficient on price itself is not significant – price movements matter but the price level itself does not. Specifications (9) and (10) perform least squares and instrumental variables regressions excluding Windsor. Windsor, as discussed next, is the one city in the dataset where weekly asymmetric price cycles are visible in the daily data. The results are not affected by the inclusion or exclusion of Windsor.[15]

4.2 Price Dispersion and Weekly Price Cycles

Next I examine search responses to price dispersion stemming from gasoline price cycles. I begin with the city of Windsor to see how search varies along the course of a weekly or biweekly price cycle. The Windsor specifications generally confirm the results of previous studies in the context of weekly price cycles but highlight a general problem in relating search activity to price cycle activity that can be difficult to handle. The weekly nature of the price cycle and the timing of price increases and decreases along it tend to be correlated with the natural weekly search cycle that would exist even in the absence of price cycles. In short, price dispersion is often greatest at points in the cycle when search normally would have been the greatest anyway. The more regular, consistent, and predictable the weekly price cycles are, the more difficult it can be to separate the price cycles and the natural search cycle econometrically.

Before exploring the issue, I estimate and report background information on the structural characteristics of the Windsor gasoline price cycle. Over the sample period, and unlike cycles in many other cities, the cycle has at times been weekly and at times been bi-weekly. The average

[14] The rack price is added as an instrument for the retail price in levels.

[15] The presence of daily price cycles in the cities in Toronto, London, and Vancouver are not of concern. The intraday variation in price dispersion is entirely washed away when aggregating the data to the daily level, and the price cycles are not visible in daily data.

duration of the cycle is 8.9 days (s.e. = 0.52). The relenting phase of the cycle (when market prices are rising) is generally complete in two days, with most stations increasing price on the first day and most the rest doing so on the second day. The amplitude of the cycle averaged 6.2 cents per liter (s.e. = 0.30).

Results on Windsor are reported in Table 4. Specification (11) is similar to the specifications in Table 2, regressing search on lead, contemporaneous, and lagged price changes, but not yet explicitly taking into account the known pattern of the cycle. Here, I find a statistically significant effect on search intensity of the day-ahead (lead) price increase. An expected one cent day-ahead increase in the price increases search by 2.7%. There is a similar effect on search of the day ahead price decrease, but it is not significant. Other effects are economically small and in most cases insignificant. In short, search intensity is highest just in advance of price increases. Part of this can be explained by consumers forecasting the next relenting phase and buying in advance of it (Noel (2012), Byrne et al. (2015)). However, part of it may be that relenting phases typically take two days, so that a lead price may simply indicate that a relenting phase is already underway, price dispersion is high, and search is high as a result.

It is straightforward to control for the timing of the cycle. In Specification (12), I add cycle day indicators $SECOND\_DAY\_PRIOR$, $FIRST\_DAY\_PRIOR$, $START\_OF\_RELENT$, END_OF_RELENT, $FIRST\_DAY\_AFTER$ and $SECOND\_DAY\_AFTER$. The mid-cycle period is omitted. I do not yet include day of the week indicator variables for expositional purposes. The results show a very large increase in search at the start of the relenting phase, 28.7% (a coefficient of 0.252). Part of the effect is spurious – relenting phase price increases often occur on the same days during the work week, a high time for search, and the omitted period (mid-cycle) tends to falls on or near a weekend, a low time for search. As a result, the estimates pick up the effect of both the price cycle and the natural weekly search cycle, and the coefficient on $START\_OF\_RELENT$ and other nearby days are likely to be biased upward.

The obvious fix is to include day of the week indicators. In Specification (13), I include day of the week indicator variables in addition to cycle day variables. The coefficient on $START\_OF\_RELENT$ is still large and significant, but is now just one-third of what it had previously been. It implies an increase in search intensity of 9.0% (coefficient of 0.086) compared to mid-cycle. The coefficient

on ONE_DAY_PRIOR falls to half of its previous value, and several other coefficients reverse signs.

However, this regression can potentially overcompensate and in turn understate the effects on search. When the price cycle and the natural search cycle are highly correlated, they are difficult to separate econometrically. Indicator variables soak up not only the natural weekly search cycle but also any price-cycle-induced increases in price dispersion that tend to repeatedly occur at the same stage of the cycle on the same day of the week. Fortunately, in the case of Windsor, cycles were sometimes weekly and sometimes biweekly, adding some variation in cycle timing to identify effects, even holding fixed the day of the week. In many cases, however, there is less variation and search effects would mainly be identified off of cycle collapses, delayed or false starts (in the language of Noel (2008)), or other missteps. While interesting, these may not be representative of how search normally responds to price dispersion changes.

Where the weekly cycle is almost perfectly synchronous with the day of the week and there is almost perfect correlation in the weekly price cycle and the natural weekly search cycle, the two are difficult to disentangle without additional restrictions and assumptions (Byrne and de Roos (2015)).

In Specification (14), I include both day of the week indicators and cycle day indicators (as in Specification (13)) as well as lead, contemporaneous, and lagged price changes (as in Specification (11)). I find a similar pattern of coefficients as previous specifications but none of the cycle day or price change coefficients are significant anymore. Essentially, all three sets of explanatory variables are trying to capture the same thing. (The vast majority of variation in the price change variables comes not from the actual size of increases or decreases, but rather whether there was an increase or a decrease in a given period at all, i.e. they are highly correlated with the cycle day and the day of the week indicators.)

4.3 Price Dispersion and Daily Price Cycles

What would be useful is a situation in which an exogenous shock either started or stopped the price cycles, so that the effect of the underlying natural search cycle could be removed and the effect of cycle-driven price dispersion on search could be measured. Fortunately, the Nanticoke refinery fire

allows that.

The impact of the fire could easily be missed examining the daily data. Price cycles in some of the larger cities in Ontario have been daily instead of weekly since 2004 (Atkinson et al. (2014)). In the three sample cities with daily price cycles, prices rise early in the morning and fall over the course of the day before rising again the next morning.

Figure 2 shows gasoline prices and margins (calculated as the difference between retail and rack prices) for the cities of Toronto, London, and Vancouver, the three cities in the sample that, at least prior to the fire, exhibited daily price cycles. The left panels show prices at the four-times-a-day level in the weeks before and after the fire. The right panels show daily margins before and after the fire over a longer period. The date of the fire is represented with a vertical line.

The left panels show that, almost immediately after February 15th, the daily price cycles in Toronto and London ceased. In Vancouver, a city not supplied by the refinery, the price cycles were unaffected. In Toronto and London, the relenting phase always occurred in the first intraday period. In Vancouver, the relenting phase also always occurred in the first intraday period noting that, on three days over the two month span, there was also a small price increase in the fourth intraday period of the day before.[16] The amplitude of the cycle was 5.5 cents per liter in Toronto and 5.2 cents per liter in London. The amplitude was 3.7 cents per liter in Vancouver.

The right panels show how margins changed after the fire. Margins increased in Toronto and London, but a notable change was that margins became less volatile. In Toronto, margins became an almost constant 5 cents per liter (Atkinson et al. (2014)). Retail prices in Toronto moved in lockstep with daily changes in the rack price across much of the city. There was some reduction in the variance of margins in London as well, but short of constant margins (Noel (2015)). Both before and after the fire, margins in Vancouver fluctuated with the ongoing cycles there.

Importantly, the disappearance of price cycles in Toronto and London means that the non-linear pattern of cycle-induced price dispersion across the four periods of the day (very high, low, low, medium) came to an abrupt halt. I test whether search intensity also fell at precisely those times of the day where price dispersion fell after the cycles ceased in those cities.

[16] I define a relenting phase as a series of consecutive price increases in which the cumulative price increase is at least one cent per liter.

For completeness, I first conduct analyses similar to that of Tables 2, 3, and 4, for the three cities with the daily cycles and using the four-times-a-day data. To focus on short run cyclical price changes, I consider lead and contemporaneous price changes and eight lagged intraday price changes. I allow potentially asymmetric responses for price increases and decreases as well. All specifications include year-month, day of the week, and city indicator variables.

In Specification (15), I regress search intensity only on lead, contemporaneous, and lagged price changes (and the above indicator variables), similar to the specifications of Tables 2 and 3. In Specification (16), I regress search intensity on intraday indicator variables, instead of price changes, to explicitly account for cycle timing. In Specification (17), I regress search intensity on both intraday indicator variables and price changes, similar to what I did for weekly cycles in Windsor in Table 4.[17]

I begin with Specification (15) which does not explicitly account for the cycle. I find a large coefficient on the contemporaneous price increase; the coefficient of 0.076 would suggest that a one-cent contemporaneous price increase would increase search intensity by 7.9%. I find a large but statistically insignificant coefficient on the lead price increase (3.5%). I find no significant coefficients in terms of a contemporaneous or lead price decrease, and smaller and insignificant effects on the other price change coefficients.

The collinearity concern with the weekly price cycle and the natural weekly search cycle is echoed here for daily price cycles and the daily search cycle. Specification (16), which includes intraday indicator periods but does not include price change variables, would suggest that the vast majority of search occurs in the first intraday period (the omitted period), when the vast majority of relenting phase price increases occur. The result is consistent with a price dispersion story but is also consistent the simple fact that there are higher traffic counts during the morning rush hour. Similarly, search is also relatively high in the fourth intraday period when prices are at their lowest and generally more disperse across stations. However, this period includes most of the evening rush hour. Search is lowest mid-cycle when price dispersion is relatively low and when there are also relatively fewer drivers on the road.

Not surprisingly, when I combine intraday indicator variables and the set of price change vari-

[17] Since rack prices change no more than once a day, they have little power in predicting intraday price changes.

ables in Specification (17), the price change coefficients all become insignificant. The price cycles are very regular, timed to the day, and there is relatively little to identify the effects of the daily price cycle separate from the natural daily search cycle. Like weekly price and search cycles in many cases, the correlation between the daily price cycles and the natural daily search cycle is high and difficult to separate.

4.4 The Natural Experiment

In this study, fortunately, I am able to separate the effect of cycle-induced search from the natural daily search cycle by exploiting the shock provided by the Nanticoke refinery fire. After the cycles ceased in Toronto and London, the pattern of price dispersion over the course of the day changed in a non-linear way, with a large relative decrease in price dispersion in the first, and potentially the fourth, intraday periods. There was no such corresponding non-linear change in Vancouver.

Table 6 reports results from two sets of specifications, a regression discontinuity specification and a difference-in-differences specification, for each city. Specifications (18) through (20) are the regression discontinuity estimations in which I regress the natural log of price reports on day of the week indicator variables, intraday indicator variables ($SECOND\_INTRADAY\_PERIOD$ through $FOURTH\_INTRADAY\_PERIOD$), and an $AFTER\_REFINERY\_FIRE$ indicator variable equal to one in periods after the February 15, 2007 fire. All specifications include monthly indicator variables.[18]

Specifications (21) through (23) are the main specifications of interest. These are the difference-in-differences specifications, one for each city, in which I regress the log of price reports on intraday indicator variables, the $AFTER\_REFINERY\_FIRE$ indicator variable, and interactions of the intraday indicator variables and the $AFTER\_REFINERY\_FIRE$ indicator variable (names abbreviated in the table for length). I include day of the week indicator variables in all specifications. These specifications test whether the distribution of search across the four intraday periods had significantly changed in Toronto and London after the fire. In particular, I test whether the degree of search intensity disproportionately fell at precisely those times during the day when price dispersion

[18] Augmented Dickey-Fuller tests on the log of intraday price reports reject the null hypothesis of a unit root in each city in favor of stationarity.

had previously been elevated in the presence of price cycles. If search responds to price dispersion, I expect search intensity to fall disproportionately in the first intraday period, and possibly to a lesser extent the fourth intraday period, in the cities of Toronto and London after the cycles ceased, but not in Vancouver.

I begin with Toronto in the regression discontinuity Specification (18). Like those for other cities, the coefficients on the intraday period indicator variables show that search intensity is generally greatest in the first intraday period, and to a lesser extent in the fourth intraday period, with the lowest levels of search occurring in the midday period.

The coefficient of interest is the $AFTER\_REFINERY\_FIRE$ indicator which shows that search intensity in Toronto decreased overall by 12.0% (coefficient -0.128) after the price cycles ceased. The estimate is statistically significant at the 5% level. The story is similar in the city of London. From Specification (19), the total number of price reports fell by 12.5% in London after the fire, significant at the 5% level. In Vancouver, where there was no change in cycling activity, the estimate is still seemingly high at 11.2%, but not statistically significant, according to Specification (20).

The result for Vancouver is not so surprising. Further inspection of the data shows that there was a general decline in the number of price reports around the time of the fire and, even with monthly indicator variables, the $AFTER\_REFINERY\_FIRE$ coefficient may pick up some of this trend. The trend was gradual in Vancouver whereas in Toronto and London the change was more distinct after February 15th. When I re-estimate Specifications (18) to (20) using a time trend variable in place of monthly indicator variables. I find the coefficient on the $AFTER\_REFINERY\_FIRE$ variable in Vancouver largely disappears, corresponding to a 3.5% decline in search, and is highly insignificant. In contrast, the coefficients only marginally decrease in Toronto and London, corresponding a 10.6% decline and a 10.4% decline, respectively.

I now turn to the main specifications of interest, the difference-in-differences Specifications (21) through (23). I test whether search intensity in Toronto and London disproportionately fell at precisely those times of the day where price dispersion had previously been the greatest before the cycles ceased. The last three columns of Table 6 report the results for the three cities. In each case, the reduction in search intensity during the first intraday period (the omitted period)

following the fire is given by the $AFTER\_REFINERY\_FIRE$ coefficient. For the other three intraday periods, it is the sum of the $AFTER\_REFINERY\_FIRE$ coefficient and the relevant interaction term.

In short, I find that search intensity in Toronto and in London significantly and disproportionately fell in the first intraday period, consistent with the decrease in price dispersion. Search intensity also decreased significantly in Toronto in the fourth intraday period, and decreased in London but not significantly so. There was little change overall in the midday periods. Also, I find no significant change in the distribution of search intensity over the course of the day in Vancouver, where price cycles continued even after the fire. The evidence suggests that the non-linear changes in search intensity was causally affected by the matching non-linear changes in price dispersion across the day after the cessation of price cycles.

I begin with Specification (21) for Toronto. The coefficient on the $AFTER\_REFINERY\_FIRE$ variable shows that search activity in the first intraday period (the omitted period) decreased by 20.0% in Toronto after the cessation of cycles (coefficient = -0.22). Summing the coefficients on the $AFTER\_REFINERY\_FIRE$ variable and the $FOURTH\_INTRADAY * AFTER$ interaction term, I find that search activity fell by 17.8% in the fourth intraday period (sum of coefficients = -0.222+0.026=-0.196). Both changes are statistically significantly different from zero at the 5% level. In contrast, there was little change in search activity in Toronto in the two mid-day periods where price dispersion had generally been the lowest. The average change in search intensity in the mid-day periods was -4.5%, insignificantly different from zero.[19] In other words, the vast majority of the decrease in search intensity came disproportionately from the periods in which the decrease in price dispersion would have been greatest, especially the first intraday period.

Specification (22) reports results for London. The coefficient on the $AFTER\_REFINERY\_FIRE$ variable shows that search intensity in London fell by 25.0% in the first intraday period after the cycles ceased. The estimate is significant at the 5% level. I find an 11.1% decrease in search activity in the fourth intraday period, though this estimate is not significantly different from zero. Search activity decreased by only 4.4% in the two mid-day periods in London overall. The majority of the

[19] The calculation is exp((-0.222*2+0.150+0.202)/2)-1. Search fell by 6.9% in the second intraday period and by 2.0% in the third intraday period, both statistically insignificant.

decrease in search intensity in London came in the first intraday period, where the relenting phases of the cycle had been and where price dispersion had been greatest.

Specification (23) reports results for Vancouver. Following the fire, and consistent with the expected non-effect, I find an insignificant decrease in search intensity in Vancouver during the first intraday period of 8.9%. More importantly, the coefficients on all the interaction variables for Vancouver are insignificantly different from zero. This shows that any decrease in search intensity in Vancouver over this period did not come disproportionately from the first or fourth intraday periods. Instead, it came proportionally from all periods within the day, consistent with the continued presence of price cycles and price dispersion patterns, and in contrast to the disproportional decreases in Toronto and London.

In summary, I conclude that search intensity does in fact respond to exogenous changes in price dispersion. I find that search intensity fell in the cities where the price cycles had stopped and disproportionately at precisely those times of day when price dispersion had fallen. It did not fall disproportionately where the cycles did not stop.

A possible concern about this conclusion stems from the fact that the cessation of cycles not only impacted price dispersion but also affected price levels in the affected cities. Noel (2015) shows that prices increased in the long run by about one cent per liter when the price cycles stopped in the affected cities. It could be argued that the observed decreases in search intensity are due to higher prices overall and not due to price dispersion.

The hypothesis is unlikely for several reasons. First, one cent per liter is a relatively small amount, and prices fluctuated over a much greater range even before the fire. Second, aggregate gasoline demand is very inelastic in the short run and a one cent per liter change in price levels is unlikely to have a meaningful effect on gasoline demand.[20] Third, the results of Specifications (7) and (8) in Table 3 show that there is no effect of price levels on search intensity. Fourth, and importantly, an increase in price levels cannot explain the temporal redistribution of search over the course of the day in the affected cities. Increased prices are felt throughout the day every day. In contrast, price dispersion predominantly changed in the first intraday period and, to a lesser extent, the fourth, and this is where the effects were found.

[20] Hughes et al. (2008) find that short run price elasticities have moved close to zero in recent decades.

To check the robustness of my findings, I perform an alternate test based on comparing the coefficient of variation of the predicted values of search intensity both before and after the fire. The natural daily search cycle implies that search intensity is likely to be greatest in the first and fourth intraday periods, even in the absence of price cycles. In the presence of price cycles, search intensity is expected to be magnified in the first and fourth intraday periods, adding to the variance in search intensity over the day. Against this backdrop, I test whether the coefficient of variation significantly decreased in Toronto and London after the fire. The null hypothesis is that there was no decrease in the coefficient of variation in any city after the fire. The alternative is that there was a decrease in the coefficient of variation after the fire in Toronto and London – i.e. search intensity became more uniform throughout the day – with no change in Vancouver.

The results confirm the main conclusion. I find that the coefficient of variation for Toronto fell from 0.058 before the fire to 0.046 after, a statistically significant decrease at the 1% level. The coefficient of variation for London also fell substantially, from 0.063 before the fire to 0.044 after, again significant at the 1% level. In contrast, the coefficient of variation for Vancouver was essentially unchanged, from 0.074 before the fire to 0.071 after (with a p-value on the difference of 0.61). I conclude that the distribution of search activity across the day did indeed become more uniform in Toronto and London after the cycles ceased, while there was no redistribution of search activity in Vancouver. This confirms earlier results.

Finally, it might be interesting to compare the effect of price dispersion due to high-frequency price cycles and that due to longer term cost processes, on search intensity. Sources of price dispersion can sometimes to be difficult to separate but the daily nature of price cycles in Toronto and London in the current study makes a comparison straightforward. The separation of effects is aided by the fact that the daily price cycle is completely contained within a single day and any variation in intraday price dispersion is washed away in the daily-level data. As a result, search responses to changes in daily costs, as measured in the daily data, can be viewed as separate from responses to intraday, cycle-driven changes.

Above, I found that search intensity fell an average of 22.5% in response to a price change of approximately 5.35 cents per liter, the average amplitude of a relenting phase in Toronto and London. I ask how search intensity would change to a price change of 5.35 cents per liter resulting

from a (relatively large) 5.35 cent per liter change in costs in those same cities. It is well known that costs are largely passed through one-to-one into prices after an uneven transition period.

Repeating Specification (1) using the daily level data for the three cities in the sample with daily price cycles, I find the effect of a contemporaneous price increase on search is 1.1% and the effect of a contemporaneous price decrease on search is 3.6%, both statistically significant at the 10% level. The effects of lagged price changes are smaller, as before, and significant only in the case of decreases. A 5.35 cent per liter increase in the rack price would result in a contemporaneous increase in search intensity of only 5.9%, but a same-sized decrease would increase contemporaneous search intensity by 19.3%, similar to the response to cycle-driven price dispersion. In other words, while spotters tend to search most during the relenting phases of daily price cycles, they also increase their search efforts when prices are generally changing due to wholesale prices, and especially when they are falling.

5 Conclusion

In this article, I examine the effect of price dispersion on actual search in a set of retail gasoline markets. I find that search responds to price dispersion, both that caused by wholesale price changes and that caused by gasoline price cycles. In terms of wholesale price changes, I find that consumers search more when prices are more volatile than when they are not. Interestingly, I find a reverse asymmetry – search increases more when prices are falling than when they are rising due to cost changes.

In terms of price dispersion from retail gasoline price cycles. I find that search varies along the path of both weekly periodic and daily periodic cycles. Search is greatest in the relenting phases of the cycle, when price dispersion at a moment in time is the greatest. However, there is potential for multicollinearity problems since relenting phases are often synchronized to the day of the week or the time of day. It can be difficult to econometrically separate the effect of cycle-driven price dispersion on search from the natural weekly and daily search cycle, without identifying effects off of unusual cycle timing changes.

In the current study, I circumvent the issue by examining a unique natural experiment in which

a refinery fire caused decades-old cycles to cease in several cities. Such a change in equilibrium between cycling and non-cycling regimes is very rare. The cessation of cycles caused a non-linear change in the price dispersion pattern over the course of the day in the affected cities, and I can use this non-linearity to identify effects. I find that search intensity decreased at precisely those times of the day when price dispersion had been highest with the cycles and had fallen most when the cycles ceased. Where price cycles were not affected by the fire, I found no similar redistribution of search efforts over the day.

This article adds to our understanding of the two-way relationship between price dispersion and search. Most previous research examines how differences in search costs or benefits cause differences in price dispersion. These are examples of a supply-side shock to search believed to affect equilibrium price dispersion. It is generally assumed that unobserved search efforts respond to these shocks in the background in expected ways.

However, price dispersion itself can vary for reasons independent of search and itself cause a demand-side response to search. When price dispersion increases independently of search, it increases the benefits of search and leads to more search. Temporal and cross-sectional price dispersion is inevitable in many industries as costs rise and fall and firms transition to new price equilibria in a staggered fashion. The degree of search response has important implications for how firms might optimally adjust or transition to higher or lower prices in both competitive and oligopolistic markets. Only a few studies have addressed this demand side search response, and a direct measure of search is necessary to do so. This article contributes to that literature. Further research would be valuable in establishing whether the same search responses hold more generally across a wider variety of industries.

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Figure 1. Daily and Weekly Retail Price Cycles

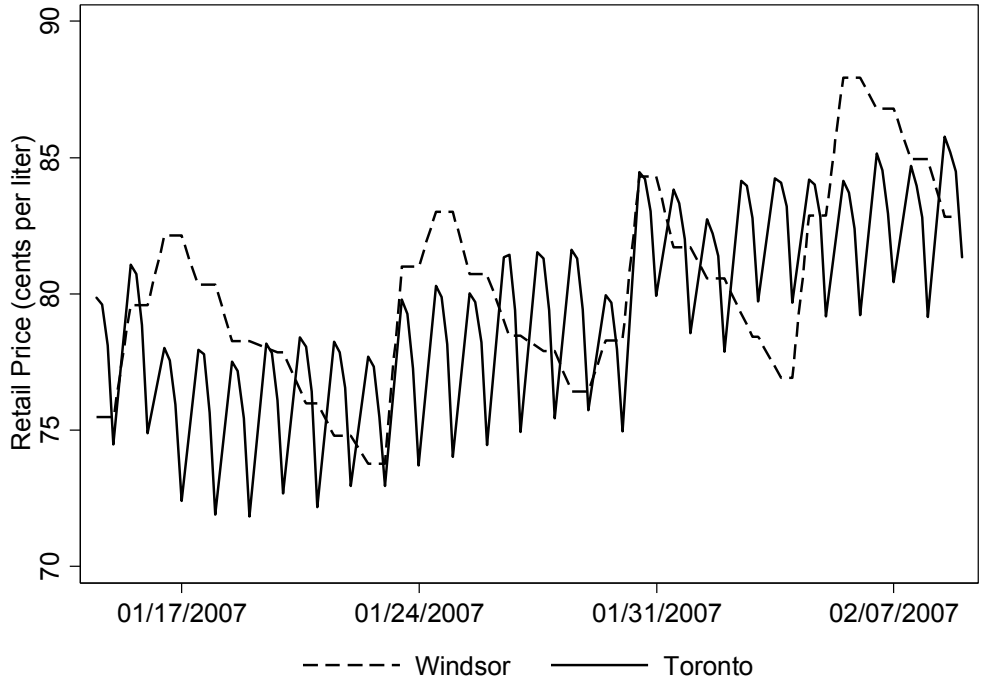
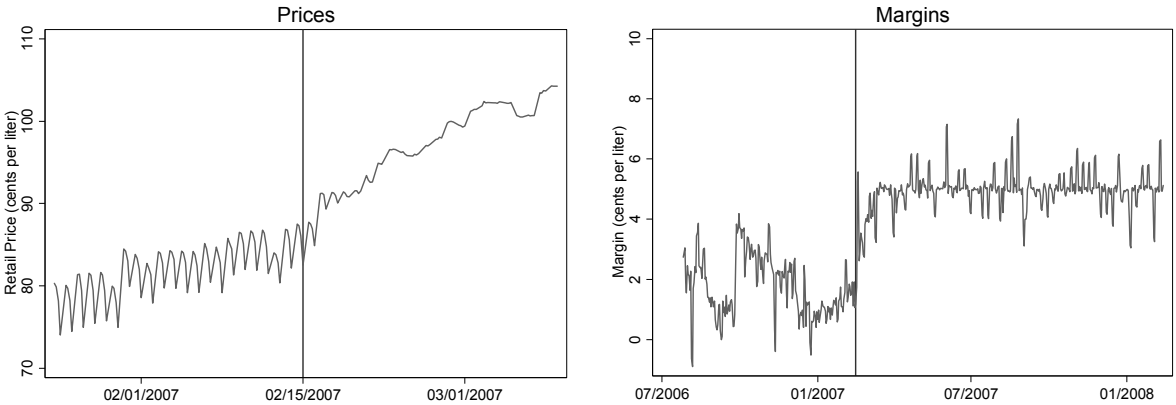
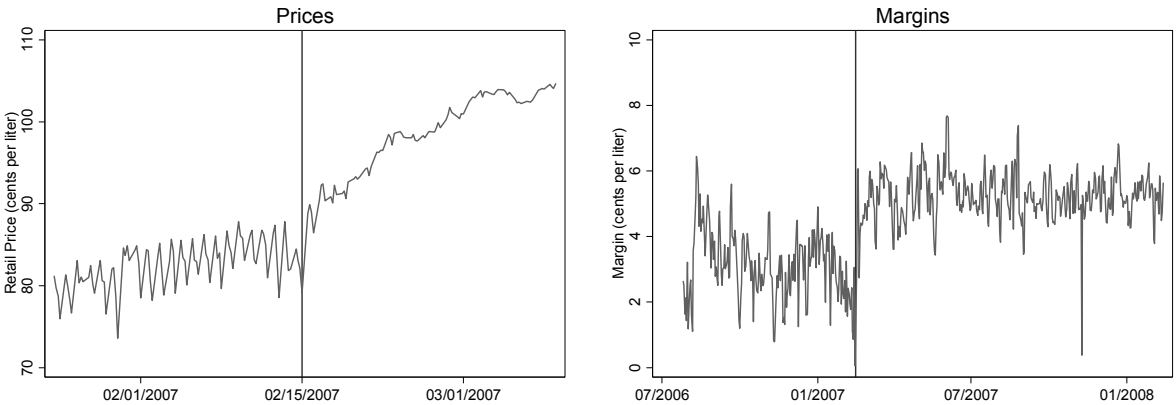


Figure 2. Prices and Margins in Sample Cities with Daily Price Cycles

Panel A: Toronto



Panel B: London



Panel C: Vancouver

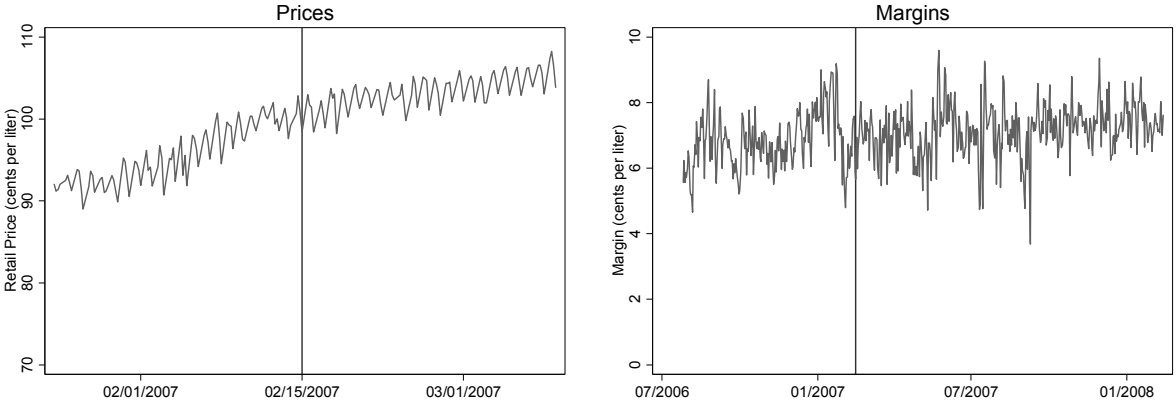


Table 1. Summary Statistics

	Mean	Std. Dev.	Minimum	Maximum
Daily Sample:				
PRICE (cents per liter)	99.20	9.83	73.76	127.96
RACK PRICE (cents per liter)	63.27	7.91	43.80	85.93
REPORTCOUNT	347.87	499.73	3.00	2297.00
Four-times-a-day Sample:				
PRICE (cents per liter)	92.48	9.99	71.83	110.09
REPORTCOUNT	131.56	150.09	2.00	670.00

Retail and rack prices in Canadian cents per liter. (Approximate exchange rate over the sample: 1 Canadian dollar = 0.9164 US dollars).

Table 2. Effects of Price Dispersion on Search Intensity

Dep. Var.: ln(ReportCount)	(1)	(2)	(3)	(4)
Δp_{t+1}^{+}	0.024**	0.025**	0.058	0.054
	(0.004)	(0.004)	(0.034)	(0.035)
Δp_{t}^{+}	0.015**	0.015**	0.036**	0.032*
	(0.004)	(0.004)	(0.013)	(0.015)
Δp_{WEEK1}^{+}	-0.008**	-0.007**	-0.007	-0.008
	(0.001)	(0.001)	(0.007)	(0.007)
Δp_{WEEK2}^{+}	-0.003*	-0.001	-0.009*	-0.006
	(0.001)	(0.002)	(0.004)	(0.004)
Δp_{t+1}^{-}	-0.021*	-0.019*	-0.091	-0.075
	(0.009)	(0.008)	(0.065)	(0.056)
Δp_{t}^{-}	-0.031**	-0.029**	-0.069**	-0.058**
	(0.011)	(0.011)	(0.015)	(0.015)
Δp_{WEEK1}^{-}	-0.006	-0.004	-0.010	-0.002
	(0.003)	(0.003)	(0.009)	(0.011)
Δp_{WEEK2}^{-}	-0.007**	-0.006*	-0.003	-0.002
	(0.002)	(0.003)	(0.006)	(0.006)
City indicators	Y	Y	Y	Y
Dow-of-week indicators	Y	Y	Y	Y
Year-month indicators	Y	N	Y	N
Time Trend	N	Y	N	Y
Num. Obs.	4355	4355	4355	4355
Adj R-squared	0.968	0.968	0.966	0.967

Standard errors in parentheses. ** Significant at the 5% level. * Significant at the 10% level.

Table 3. Effects of Price Dispersion on Search Intensity: Robustness Checks

Dep. Var.: ln(ReportCount)	(5)	(6)	(7)	(8)	(9)	(10)
Δp_{t+1}^{+}	0.025**	0.054	0.023**	0.058	0.022*	0.027**
	(0.004)	(0.035)	(0.004)	(0.034)	(0.009)	(0.008)
Δp_{t}^{+}	0.015**	0.032*	0.015**	0.036**	0.011	0.029*
	(0.004)	(0.015)	(0.004)	(0.012)	(0.009)	(0.013)
Δp_{WEEK1}^{+}	-0.007**	-0.008	-0.007**	-0.007	-0.005	-0.002
	(0.001)	(0.007)	(0.002)	(0.007)	(0.004)	(0.005)
Δp_{WEEK2}^{+}	-0.001	-0.006	-0.002	-0.008*	-0.005	-0.009
	(0.002)	(0.004)	(0.001)	(0.004)	(0.003)	(0.005)
Δp_{t+1}^{-}	-0.019*	-0.075	-0.021*	-0.092	-0.025	-0.044**
	(0.009)	(0.056)	(0.009)	(0.065)	(0.014)	(0.011)
Δp_{t}^{-}	-0.029**	-0.057**	-0.030**	-0.069**	-0.037**	-0.056**
	(0.011)	(0.015)	(0.011)	(0.015)	(0.013)	(0.007)
Δp_{WEEK1}^{-}	-0.004	-0.002	-0.005	-0.010	-0.007	-0.015*
	(0.003)	(0.011)	(0.004)	(0.009)	(0.005)	(0.007)
Δp_{WEEK2}^{-}	-0.006**	-0.002	-0.006*	-0.003	-0.008	-0.005
	(0.002)	(0.006)	(0.003)	(0.006)	(0.004)	(0.005)
p_t			-0.001	-0.001		
			(0.002)	(0.002)		
City indicators	Y	Y	Y	Y	Y	Y
Dow-of-week indicators	Y	Y	Y	Y	Y	Y
Year-month indicators	N	N	Y	Y	Y	Y
Time Trend	Quadratic	Quadratic	N	N	N	N
Num. Obs.	4355	4355	4355	4355	3627	3627
Adj R-squared	0.968	0.967	0.968	0.966	0.970	0.969

Standard errors in parentheses. ** Significant at the 5% level. * Significant at the 10% level.

Table 4. Effects of Price Dispersion on Search in Windsor

Dep. Var.: ln(ReportCount)	(11)	(12)	(13)	(14)
TWO_DAYS_PRIOR		-0.161**	-0.044	-0.049
		(0.052)	(0.044)	(0.045)
ONE_DAY_PRIOR		0.057	0.030	-0.001
		(0.052)	(0.045)	(0.059)
START_OF_RELENT		0.252**	0.086*	0.063
		(0.052)	(0.045)	(0.070)
END_OF_RELENT		0.084	-0.073	-0.065
		(0.052)	(0.045)	(0.060)
ONE_DAY_AFTER		0.036	-0.053	-0.036
		(0.053)	(0.046)	(0.048)
SECOND_DAY_AFTER		0.000	-0.044	-0.024
		(0.054)	(0.047)	(0.048)
Δp_{t+1}^{+}	0.027**			0.018
	(0.011)			(0.014)
Δp_{t}^{+}	0.000			0.001
	(0.011)			(0.014)
Δp_{WEEK1}^{+}	-0.009*			-0.008
	(0.005)			(0.005)
Δp_{WEEK2}^{+}	-0.006			-0.006
	(0.005)			(0.005)
Δp_{t+1}^{-}	-0.023			-0.032
	(0.024)			(0.025)
Δp_{t}^{-}	-0.011			-0.013
	(0.024)			(0.025)
Δp_{WEEK1}^{-}	0.007			0.006
	(0.010)			(0.010)
Δp_{WEEK2}^{-}	0.013			0.014
	(0.011)			(0.011)
Dow-of-week indicators	Y	N	Y	Y
Year-month indicators	Y	N	Y	N
Num. Obs.	728	730	730	728
Adj R-squared	0.422	0.172	0.422	0.421

Standard errors in parentheses. ** Significant at the 5% level. * Significant at the 10% level.

Table 5. Effects of Price Dispersion on Search in Cities with Daily Price Cycles

Dep. Var.: ln(ReportCount)	(15)	(16)	(17)
SECOND_QUARTER		-0.479**	-0.429*
		(0.064)	(0.101)
THIRD_QUARTER		-0.325	-0.280*
		(0.147)	(0.093)
FOURTH_QUARTER		-0.112	-0.020
		(0.046)	(0.010)
Δp_{t+1}^{+}	0.030**		-0.021
	(0.014)		(0.013)
Δp_{t}^{+}	0.078**		0.020
	(0.016)		(0.008)
Δp_{WEEK1}^{+}	-0.006		0.002
	(0.013)		(0.006)
Δp_{WEEK2}^{+}	-0.007		-0.007
	(0.009)		(0.006)
Δp_{t+1}^{-}	0.015		0.007
	(0.018)		(0.023)
Δp_{t}^{-}	-0.014		-0.012
	(0.023)		(0.016)
Δp_{WEEK1}^{-}	0.027*		0.005
	(0.015)		(0.006)
Δp_{WEEK2}^{-}	-0.012		-0.014
	(0.010)		(0.006)
City indicators	Y	Y	Y
Dow-of-week indicators	Y	Y	Y
Year-month indicators	Y	Y	Y
Num. Obs.	650	660	650
Adj R-squared	0.848	0.863	0.863

Standard errors in parentheses. ** Significant at the 5% level. * Significant at the 10% level.

Table 6. Effects of Price Dispersion on Search: A Natural Experiment

Dep. Var.: ln(ReportCount)	Toronto (18)	London (19)	Vancouver (20)	Toronto (21)	London (22)	Vancouver (23)
SECOND_INTRADAY_PERIOD	-0.500**	-0.383**	-0.582**	-0.566**	-0.566**	-0.592**
	(0.056)	(0.071)	(0.086)	(0.074)	(0.093)	(0.115)
THIRD_INTRADAY_PERIOD	-0.588**	-0.339**	-0.067	-0.676**	-0.349**	-0.031
	(0.056)	(0.071)	(0.086)	(0.074)	(0.093)	(0.115)
FOURTH_INTRADAY_PERIOD	-0.070	-0.210**	-0.079	-0.081	-0.284**	-0.060
	(0.056)	(0.071)	(0.086)	(0.074)	(0.093)	(0.115)
AFTER_REFINERY_FIRE	-0.128**	-0.134*	-0.119	-0.222**	-0.287**	-0.094
	(0.060)	(0.076)	(0.091)	(0.091)	(0.114)	(0.140)
SECOND_INTRADAY * AFTER				0.150	0.421**	0.023
				(0.113)	(0.141)	(0.174)
THIRD_INTRADAY * AFTER				0.202*	0.024	-0.081
				(0.113)	(0.141)	(0.174)
FOURTH_INTRADAY * AFTER				0.026	0.169	-0.044
				(0.113)	(0.141)	(0.174)
Dow-of-week indicators	Y	Y	Y	Y	Y	Y
Year-month indicators	Y	Y	Y	Y	Y	Y
Num. Obs.	220	220	220	220	220	220
Adj R-squared	0.513	0.199	0.222	0.516	0.230	0.212

Standard errors in parentheses. ** Significant at the 5% level. * Significant at the 10% level.